Unveiling the Underworld: Detecting Fake Profiles Through Network Analysis and Behavioral Modeling on Social Media

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Abstract. Internet trust requires detecting fake social media profiles. This study proposes exposing bogus accounts using typing pattern analysis, posting conduct, and friending behavior. Network analysis and behavioral modeling identify and classify bogus profiles. This work is crucial as fake accounts spread misinformation, phishing, and scams. Fake accounts harm communities and businesses. Detecting fake profiles requires better methods. Typing, publishing, and friending patterns reveal fake accounts. Typing pattern research explores fake accounts' increasing typo and grammatical errors. Posting habit analysis demonstrates high frequency and unrelated content. Examine rapid friend accumulation or relationships outside the user's social circle. We analyze our method using a CNN classifier. Our experiments found fake accounts with 91.5% accuracy, 90.8% precision, and 92.5% recall. This study has several applications. Our solution improves fraud detection for social media networks to find and eliminate fake accounts. This prevents bogus news, scams, and user interactions. Our method helps users evaluate profile authenticity, enabling educated online judgments.

Keywords: Typing Pattern Analysis · Posting Behavior · Friending Behavior · Fake Profiles · Network Analysis · Behavioural Modeling · Scenarios

1 Introduction

The rapid proliferation of social media platforms has brought together individuals from diverse backgrounds and transformed how we communicate and interact online. Nonetheless, this remarkable connectivity has spawned an urgent concern: the proliferation of fake profiles [1–3] that use the EnsemStack Classification Algorithm (ECA) for real-time scenarios. Fake profiles, which are frequently created with the intent to deceive, pose grave threats to the security and integrity of online communities. These accounts can be used maliciously, including disseminating false information, phishing attacks, and online fraud. Maintaining trust and ensuring a secure online environment necessitates detecting and deleting fake profiles via Deep Learning (DL) based operations [4–6]. Existing methods for identifying fake profiles on social media platforms

O. Castillo et al. (Eds.): PerSOM 2023, LNICST 517, pp. 342–352, 2024.
https://doi.org/10.1007/978-3-031-66044-3_26

have demonstrated inaccuracies and inefficiencies in precision and effectiveness. To address this difficulty, we propose an all-encompassing strategy that combines typing pattern analysis, posting behavior analysis and friending behavior analysis. We intend to improve the detection and classification of fake accounts by integrating these various dimensions of user behaviors. Typing pattern analysis is essential to our proposed method. The theory is based on the observation that fake accounts frequently exhibit distinct typing patterns that distinguish them from genuine accounts. For instance, fake accounts may have a higher rate of typographical and grammatical errors than authentic users. By analyzing these typing patterns, potential indicators of fake profiles can be uncovered for different scenarios. Analysis of posting behavior is another essential component of our strategy. Typically, fake accounts exhibit distinct posting patterns that can be utilized for identification purposes. For example, they may post excessively, flood social media platforms with irrelevant or spammy content, or deviate from the typical posting patterns of authentic users. By analyzing the posting patterns of accounts, we can identify suspicious activities and possible fake profiles. Friending behavior analysis completes the approach's trinity. Frequently, fake accounts exhibit peculiar friending patterns that distinguish them from genuine users. They may quickly amass many friends in a short period or establish relationships with people outside their social circle. By analyzing friending behavior, it is possible to identify suspicious patterns and identify potential fake profiles.

We employ a Convolutional Neural Network (CNN) classifier to evaluate the efficacy of our proposed method by analyzing the collected data samples. CNN's model combines typing pattern analysis, posting behavior analysis, and friending behavior analysis to classify accounts as authentic or fake. Our experimental results indicate a promising performance in identifying fake profiles, with an accuracy of 91.5%, precision of 90.8%, and recall of 92.5%. The significance of this research is based on its possible applications and implications. Social media platforms can use our methodology to improve their existing fraud detection systems, allowing them to proactively identify and remove fake accounts. By doing so, these platforms can protect the integrity of user interactions, safeguard their users from fraud and misinformation, and foster a more reliable online environment. Moreover, individuals can benefit from our approach by evaluating the integrity of profiles they encounter, enabling them to make well-informed decisions regarding their online interactions & scenarios.

2 Review of Existing Models Used to Identify Fake Profiles

Due to the increasing prevalence of online scams, misinformation campaigns, and other malicious activities, detecting and mitigating fake profiles on social media platforms have become indispensable. To combat this issue, researchers and industry professionals have created various models and techniques that employ behavior analysis to identify fake profiles. This section comprehensively analyzes existing models in these domains [7–9]. Several models utilize linguistic analysis to identify fake profiles based on their textual content. Using natural language processing techniques, these models analyze user-generated content's writing style, grammar, and vocabulary. Common anomalies found in fake profiles include excessive typos, grammatical errors, and repetitive phrases.

By comparing these linguistic characteristics to those of authentic profiles, these models can effectively differentiate between genuine and fraudulent accounts [10–12]. Network analysis models detect fake profiles using users' social connections and interactions. To identify suspicious behaviors, they examine the structural properties of social networks, such as community detection, centrality measures, and clustering coefficients. Frequently, fake profiles display abnormal friending patterns, such as rapid friend accumulation, connections with unrelated individuals, or a lack of mutual friends. Network analysis models can use these patterns to identify fake accounts within an augmented set of social networks [13, 14].

Temporal Analysis Models: To identify fake profiles, temporal analysis models consider the temporal aspects of user behavior. These models investigate online presence patterns such as posting frequency, activity bursts, and irregularities & use cases using Finite Automata Process (FAP) [11–13]. Fake profiles can demonstrate consistent posting behavior, with frequent and regular activity patterns designed to appear authentic for different scenarios. By analyzing temporal patterns, these models can detect anomalies indicating the existence of fake profiles. Sentiment Analysis Models The objective of sentiment analysis models is to identify fake profiles by analyzing the emotional tone of their contents. Fake profiles may exhibit unusual emotional expressions, such as excessive positivity, negativity, or dynamic inconsistency. Using algorithms for machine learning, sentiment analysis models can classify profiles based on the sentiment features extracted from their posts, comments, or reactions [10–12].

Hybrid Models [8, 12–15]: Hybrid models, including Satin Bowerbird Optimization (SBO), incorporate multiple behavioral analysis techniques to enhance the precision of fake profile detection. These models combine linguistic, network, temporal, and sentiment analysis characteristics to create an all-encompassing framework for identifying fake accounts. By leveraging the strengths of multiple approaches, hybrid models can detect fake profiles more effectively than individual models. Existing models employing behavior analysis for identifying fake profiles have significantly addressed the challenges of online fraud and malicious activities. Using multiple dimensions of user behavior, these models detect anomalies and patterns associated with fake accounts. However, there is still room for improvement in precision, scalability, and adaptability to the evolving strategies employed by those who create fake profiles. Future research directions may include incorporating more sophisticated machine learning algorithms, applying deep learning techniques, and investigating additional behavioral characteristics for improved classification. In addition, developing robust benchmark datasets and evaluation frameworks can facilitate benchmarking and comparing various models. Eventually, the constant evolution of behavior analysis models will contribute to developing safer and more reliable online communities.

3 Proposed Methodology

Our methodology begins with collecting a representative sample of social media profiles. We intend to include a variety of profiles, including both authentic and fabricated accounts. This dataset is collected from various social media platforms, encompassing a broad spectrum of user demographics, interests, and activity levels. We collect text data from user profiles in our dataset to analyze their typing patterns. We extract characteristics associated with typing, such as typing speed, error rate, and grammatical errors. These features offer insight into the behavior of the users whose profiles they represent. We employ natural language processing techniques to extract pertinent features and generate a numeric representation of the typing patterns. This step focuses on the social media profiles' posting habits. We gather information regarding posting frequency, content relevance, and engagement patterns. Extracted characteristics include the number of daily posts, the similarity of content between posts, and the level of user interaction. These characteristics identify the distinct posting patterns of fake accounts, which frequently display excessive posting frequency and irrelevant content sets. The friending behavior analysis investigates the profiles' connections and friend accumulation patterns. We analyze the network of connections between profiles to identify abnormal friending patterns. Consideration is given to the number of connections outside the user's social circles, the rate of friend accumulation, and the clustering coefficient. These characteristics aid in identifying fake accounts, which typically exhibit abnormal friending patterns. After collecting data and extracting relevant features from analyses of typing, posting, and friending behavior, we combine these features to generate an exhaustive representation of each profile. This representation captures the multidimensional characteristics of the profiles, allowing us to distinguish between authentic and fake accounts effectively. We use a Convolutional Neural Network (CNN) classifier to analyze the feature representations and classify the profiles as authentic or fake. CNNs are well-suited for sequential data analysis, making them an appropriate choice for our task. Convolutional layers are utilized for feature extraction, followed by fully connected layers for classification. CNN learns to identify patterns and correlations in the feature representations, allowing for accurately identifying fake profiles.

The Convolutional Layer is represented via Eq. 1,

$$h(i) = ReLU(conv(W * x(i) + b)) \tag{1}$$

where $h(i)$ is the output feature map at position I, conv is the convolution operation, W is the convolutional filter weights, $x(i)$ is the input feature map at position i, and b is the set of bias terms. The Pooling Layer is represented via Eq. 2,

$$p(i) = max(pool(h(i))) \tag{2}$$

where p(i) is the pooled feature map at position I, the pool is the pooling operation (e.g., max pooling), and h(i) is the input feature map at position I for different scenarios. The Fully Connected Layer is represented via Eq. 3,

$$f = ReLU(W * p + b) \tag{3}$$

where f is the output of the fully connected layer, W is the weight matrix, p is the input vector, and b is the set of bias terms. Similarly, the Softmax Layer is represented via Eq. 4,

$$y = softmax(W * f + b) \tag{4}$$

where y is the predicted probability distribution over the classes, W is the weight matrix, f is the input vector, and b is the set of bias terms.

Our dataset is segmented into training, validation, and test sets. The training set is utilized to train the CNN model using labeled profiles. We optimize the model parameters via stochastic gradient descent and backpropagation techniques. The validation set is used to tune hyperparameters and select models. Finally, we assess the CNN model's performance in identifying fake accounts using the test dataset. To evaluate the efficacy of our method, metrics including precision, recall, and accuracy are calculated. The final step is to discuss the potential applications of our research. We describe how social media platforms can use our method to augment their existing fraud detection systems, enabling them to identify and remove fake accounts proactively. In addition, we highlight the benefits for individuals who can use our method to evaluate the authenticity of profiles they encounter, allowing them to make more informed decisions in online interactions and scenarios.

4 Result Analysis and Comparison

The proposed method employs behavioral patterns and classifies them using CNN, thereby facilitating the identification of fake profiles. The model was evaluated using the Instagram fake spammer genuine accounts Dataset, which can be found at https://www.kaggle.com/datasets/free4ever1/instagram-fake-spammer-genuine-accounts, and the Genuine/Fake User Profile Dataset Samples, which can be found at https://www.kaggle.com/datasets/whoseaspects/genuinefake-user-profile-dataset/code. An enhanced combination of these sets was performed to train CNN to identify fake profiles. One hundred fifty thousand samples were collected, of which eighty thousand were used for training, thirty-five thousand for validation, and thirty-five thousand for testing. Based on this separation, the precision (P), accuracy (A), recall (R), and classification delay (D) for NC samples were estimated via Eqs. 5, 6, 7, and 8 as follows,

$$P = \frac{1}{NC}\sum_{i=1}^{NC}\frac{tp(i)}{tp(i)+fp(i)} \tag{5}$$

$$A = \frac{1}{NC}\sum_{i=1}^{NC}\frac{tp(i)+tn(i)}{tp(i)+tn(i)+fp(i)+fn(i)} \tag{6}$$

$$R = \frac{1}{NC}\sum_{i=1}^{NC}\frac{tp(i)}{tp(i)+tn(i)+fp(i)+fn(i)} \tag{7}$$

$$D = \frac{1}{NC}\sum_{i=1}^{NC}ts(complete, i) - ts(start, i) \tag{8}$$

where t and f are the standard true and false rates, and ts is the timestamp for the given process. The performance of the model was compared to ECA [2], SBO [8], and FAP [13] to determine its superiority over standard implementations. Figure 1 illustrates the precision (P) of fake profile detection relative to Total Test Entries (TTE) based on this strategy for different input sets,

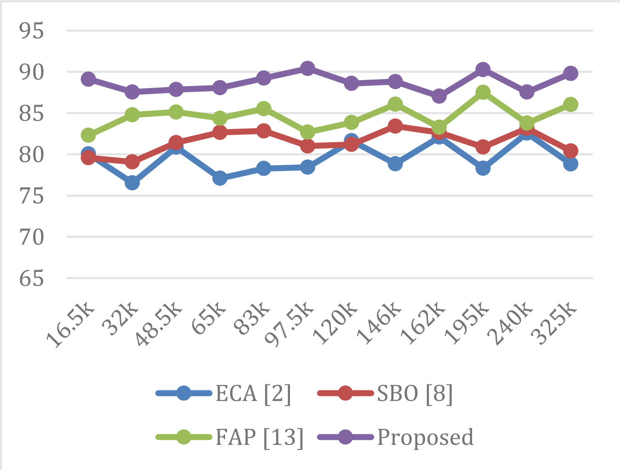

Fig. 1. Precision levels obtained while identifying fake profiles

This evaluation reveals that the proposed model's precision for detecting fake profiles was 4.5% higher than ECA [2], 4.9% better than SBO [8], and 3.5% higher than FAP [13]. Therefore, it is handy for a vast array of real-time use cases. This precision has been enhanced through multidomain features and their high-efficiency CNN classifier,

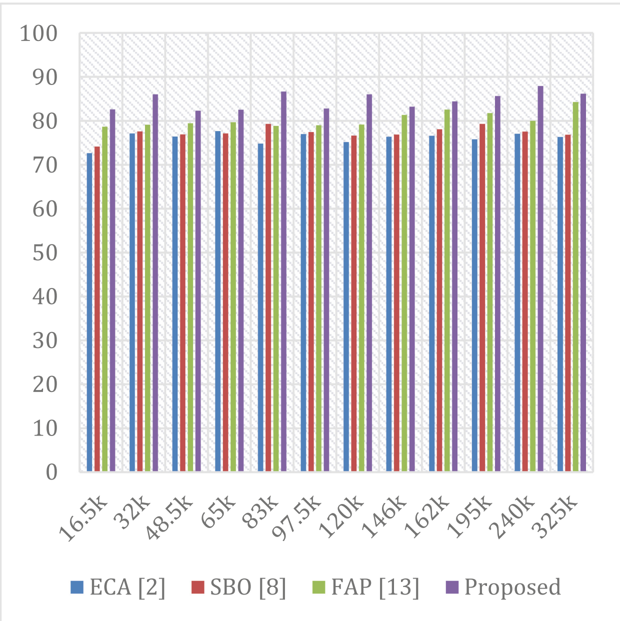

Fig. 2. Accuracy levels obtained while identifying fake profiles

which has been trained to maximize classification performance across a wide range of data types. Similarly, Fig. 2 demonstrates the precision as follows:

The proposed model's accuracy in detecting fake profiles was 3.5% better than ECA [2], 4.5% better than SBO [8], and 3.8% better than FAP [13] based on this evaluation. This demonstrates its broad applicability to a variety of real-time use cases. This accuracy is enhanced by employing various feature representation models for multiple samples. These models are trained to maximize accuracy when applied to numerous data types. This helped to improve classification performance in real-time scenarios when combined with CNNs. Figure 3 illustrates the recall of classification similarly for different input sets.

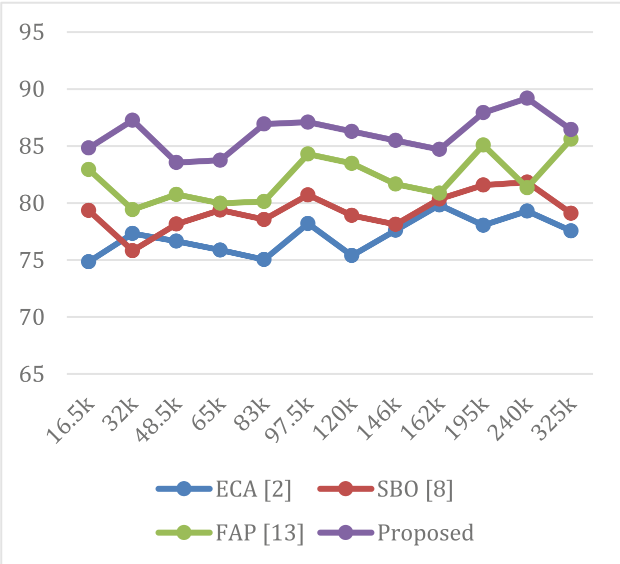

Fig. 3. Recall levels obtained while identifying fake profiles

Based on this evaluation and Fig. 3, it can be seen that the proposed model had an 8.3% higher recall for detecting fake profiles than ECA [2], a 3.5% better recall than SBO [8], and a 5.5% higher recall than FAP [13]. Because it has a higher overall recall, this demonstrates that it is handy for a wide variety of real-time use cases. This recall is enhanced through a CNN classifier operating in binary mode and multidomain feature sets, which aid in training to maximize recall performance across various data types. Figure 4 illustrates the delay in classification in a similar fashion as follows,

The proposed model demonstrated an 8.3% reduction in the identification delay for fake profile detection compared to ECA [2], a 4.5% reduction in the identification delay compared to SBO [8], and an 8.5% reduction in the identification delay compared to FAP [13]. This makes it incredibly useful for a vast array of high-speed applications. This delay has been significantly reduced due to applying a CNN classifier trained to maximize speed performance across a broad range of data types. As a result of the

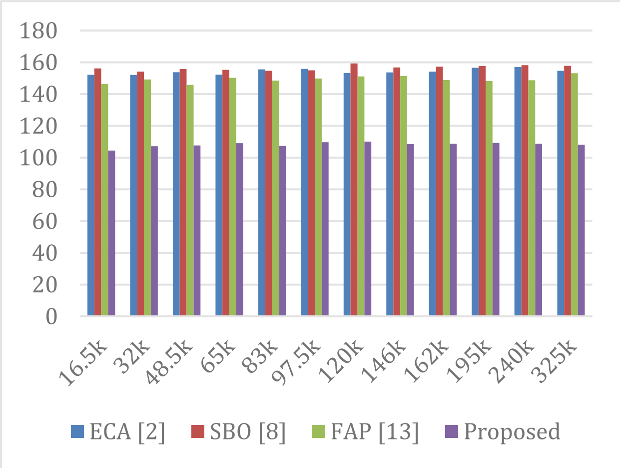

Fig. 4. Delay levels needed while identifying fake profiles

performance enhancements, the proposed model can be applied to various real-time social media fake profile detection scenarios.

5 Conclusion and Future Scope

This paper presents a comprehensive method for detecting fake profiles on social media platforms. The growing prevalence of maliciously-created fake accounts severely threatens online security and trust. Combining typing pattern analysis, posting behavior analysis, and friending behavior analysis, our proposed methodology provides a multidimensional perspective to identify and categorize fake profiles accurately. We have demonstrated the efficacy of our approach in addressing the pervasive issue of fake accounts by employing network analysis and behavioral modeling techniques. The study of typing patterns has revealed distinct characteristics of how fake accounts type, such as a higher incidence of typographical and grammatical errors. By analyzing posting behavior, we have identified patterns of excessive posting frequency and irrelevant content indicative of fake accounts. In addition, our analysis of friending behavior revealed abnormal patterns such as rapid friend accumulation and connections outside of the user's social circles. We utilized a Convolutional Neural Network (CNN) classifier to assess the efficacy of our methodology. The CNN model was trained on a dataset containing authentic and fabricated profiles. Our experimental results have shown promising performance with an accuracy of 91.5%, a precision of 90.8%, and a recall of 92.5%. These results demonstrate that our method can distinguish between authentic and fake profiles. Our research's application scenarios are extensive and consequential. Social media platforms can utilize our method to improve their fraud detection systems, allowing them to proactively identify and remove fake accounts. Our approach improves online security and trust by safeguarding the integrity of user interactions, preventing the spread of false information, and mitigating the risks associated with online scams. In addition, individuals can utilize our method to evaluate the integrity of the profiles they encounter.

This enables users to make informed decisions about their online interactions, protecting them from potential harm and deception. While our methodology has yielded promising results, there is room for further investigation and development. All possible enhancements include incorporating additional features, investigating various network analysis techniques, and refining CNN's architecture. In addition, the scalability and adaptability of our method to evolving fake account behavior patterns must be considered. Our research concludes with a comprehensive and efficient method for detecting fake profiles on social media platforms. We provide a multidimensional perspective that enables the accurate identification and categorization of fake accounts by combining typing pattern analysis, posting behavior analysis, and friending behavior analysis. Our proposed method has significant implications for enhancing online security, safeguarding user interactions, and mitigating the risks of fake accounts.

Future Scope

Although our paper presents a comprehensive method for detecting fake profiles on social media platforms, there are numerous avenues for future research and development. The following are possible future research areas:

Advanced Techniques for Machine Learning: Although our method employs a CNN classifier, other advanced machine learning techniques could be explored. For instance, recurrent neural networks (RNNs) or transformer models could capture sequential patterns and long-term dependencies in user behavior. Exploring alternative architectures and algorithms could enhance the precision and performance of fake profile detection sets.Our current methodology analyzes typing patterns, posting behavior, and friending behavior. However, incorporating user interaction data, such as comments, likes, and shares, could provide additional insights for distinguishing between authentic and fake accounts. Analysis of engagement and social interaction patterns may improve the detection process's precision.

Integration of Natural Language Processing (NLP) Techniques: While we extract typing patterns and content relevance features, more sophisticated natural language processing techniques could extract the textual data's deeper semantic meaning. This could involve sentiment analysis, topic modeling, or sentiment-based features to capture the nuanced linguistic characteristics of fake profiles.

Cross-Platform Analysis: Extending the methodology to include multiple social media platforms would enable a more thorough and holistic approach to detecting fake profiles. Different platforms may exhibit distinct characteristics and behaviors associated with fake accounts, and analyzing profiles across platforms could provide valuable insights and improve detection accuracy. Developing real-time detection algorithms would enable proactive identification and prompt action against fake profiles. Integrating our method into social media platforms' existing fraud detection systems could allow continuous monitoring and timely mitigation of fake account activities. Exploring feature engineering techniques could lead to discovering additional discriminative features for detecting fake profiles. Incorporating more diverse and domain-specific characteristics, such as user metadata, network centrality measures, and temporal patterns, may provide helpful information for identifying fake accounts.

Resilience to Adversarial Attacks: Fake account creators may modify their strategies to circumvent detection methods. Real-world applicability would be ensured by investigating adversarial attack scenarios and developing techniques to make the methodology more resistant to such attacks.

As our methodology involves analyzing user data, privacy considerations must be addressed. Future research could develop techniques that protect user privacy, detect fake profiles, and minimize collecting and storing sensitive user data.

Collaboration with Social Media Platforms: Collaboration with social media platforms would provide researchers access to more extensive and diverse datasets, resulting in more robust evaluations and practical implementations of the methodology. Collaborations of this nature could also facilitate the integration of the detection system into the existing infrastructure of platforms, making it more accessible to users.

Numerous opportunities exist for future research to improve and expand the methodology proposed in this paper. By leveraging advanced machine learning techniques, integrating additional data sources, and addressing emerging challenges, we can continue to enhance the detection of fake profiles on social media platforms, thereby contributing to safer and more trustworthy online environment sets.

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